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Multi-dimensional intervention model design for improving the clinical teaching ability of teachers in general practice standardized training base

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SUMMARY: *This study proposed an intervention model for improving the teaching ability of teachers in general practice standardized training bases through intelligent computing and decision support. Focusing on the scenes of teaching rounds, case discussion, outpatient guidance and skill teaching, a data set containing 126 teachers from 8 general practice standardized training bases, 18,640 behavior records, 4,320 trainees 'feedback and 1,260 structured evaluation forms was constructed. The teaching frequency, interaction intensity, supervision stability and feedback consistency are encoded by the timing feature representation module, and the intervention suggestions for different ability shortboards are generated by the adaptive scheduling algorithm. A system consisting of data access layer, capability analysis layer, decision service layer and interactive application layer was developed to support data maintenance, identification, intervention allocation and result tracking. Experimental results show that the accuracy of this method is 93.1%, the F1 value is 91.8%, and the average response time is 1.4 s. It has good application and deployment value in complex clinical teaching scenarios.*

KEYWORDS: *Clinical teaching ability; Multi-source teaching data; Intelligent intervention strategy; Decision support system*

1 Introduction

The standardized training of residents has become the core link of the medical personnel training system. The clinical teaching ability of the teachers in the standardized training base directly affects the organization quality of case explanation, outpatient teaching, ward round, operation demonstration and comprehensive evaluation. General practice emphasizes continuous care, first visit management, health management and community collaboration. Teaching activities include multiple tasks such as knowledge transfer, clinical judgment demonstration, communication and feedback, and process supervision. With the digital accumulation of teaching platforms, teaching records of electronic medical records, student feedback forms and process evaluation data, the use of computer methods for structural representation, pattern recognition and strategy push of teachers' teaching behavior is becoming an important technical path for the teaching governance of standardized training bases.

Khosravi et al. studied the key dimensions of explainable artificial intelligence in the field of education, and proposed an explanation framework oriented to educational scenarios, which provided a method reference for the transparent expression of teaching decision-making models [1]. Cukurova et al. proposed a learning analysis method for online one-to-one teaching quality

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monitoring, which realizes the classification of teaching sessions by identifying teachers 'behaviors, and provides a transferable idea for the quantification of teaching behaviors [2]. Furlan et al. applied learning analysis to clinical diagnostic reasoning training, and constructed analysis indicators with the help of a virtual patient simulator based on natural language processing, indicating that the medical teaching process could be transformed into computable behavioral evidence [3]. Wollny et al. studied the expectations of European students on learning analytics and pointed out that data usage, feedback methods and participation boundaries would affect the acceptance of analytics tools [4]. Farrow discussed the applicable boundary of educational interpretable AI from the socio-technical perspective, emphasizing the need to form a coordinated relationship between algorithm interpretation, trust in use and educational context [5].

In the research on the combination of prediction and intervention, Kaur et al. proposed a prediction model of student academic performance based on machine learning, which proved that ensemble learning could provide prospective basis for teaching support [6]. Krive et al. constructed an artificial intelligence curriculum integration scheme for medical education, and embedded competency-oriented content into the medical training process, which reflected the practical value of the integration of computational thinking and clinical teaching in the medical scene [7]. Alfredo et al. systematically reviewed the research on human-centered learning analytics and artificial intelligence in education, and pointed out that the system design needs to take into account control, security, reliability and trust mechanism [8]. Pan et al. reviewed the study on learning analysis intervention integrated into learning management system and showed the application trend of data-driven intervention in teaching support, learning feedback and behavior guidance [9]. The existing results have provided a solid foundation for educational analysis, medical teaching computing support and intelligent feedback, and also provided technical clues for improving the teaching ability of teachers in general practice standardized training bases.

Based on the above research basis, this paper incorporated ward round teaching, outpatient guidance, case discussion, skill training and student feedback into a unified data description framework, constructed a multi-source clinical teaching behavior and teaching process feature representation model, and designed teaching intervention strategy generation and adaptive scheduling algorithms on this basis. In order to enhance the deployability of the model, this paper further designs a multi-dimensional intervention mechanism and system implementation process combined with the decision support architecture, so that the calculation of teacher portraits, intervention task assignment, result tracking and feedback writeback form a closed loop. This study transformed the experience judgment in clinical teaching management into a technical process that could be analyzed, calculated and verified, and provided a realization path with information characteristics for improving the clinical teaching ability of teachers in general practice standardized training bases. At the same time, the system interface retains the functions of rule configuration, index iteration and visual display. Different standardized training bases can combine specific scenarios such as outpatient teaching, teaching rounds, case discussion and skill training to complete parameter adaptation and process access, and continuously track and write back the intervention results.

2 Related work

Explainable decision support, artificial intelligence in education, medical information education, and clinical training feedback together form the immediate technical context of this study. Related research has shifted from experience summary to data-driven collaborative path of representation, prediction, explanation and intervention, which provides a clear methodological basis for the computational modeling of clinical teaching ability improvement of general practice standardized training base teachers. At the same time, most of these studies have proved that the value of the teaching support system is no longer limited to the presentation of results, but lies in the integration of the original scattered behavior records, text feedback, process evaluation and task scheduling into a sustainable running data chain, so that the evaluation and intervention can be consistent in the same computing framework. This change makes related research begin to pay more attention to system cascade and closed-loop execution. The reference value is obvious.

Kostopoulos et al. studied the general progress of interpretable artificial intelligence decision support systems, and proposed that transparency, traceability and trusted output are important conditions for intelligent decision systems to be deployed in practice, and systematically summarized rule interpretation, feature contribution analysis and user-oriented visual expression [10]. The research shows that the teaching intervention system should not only give the recommendation results, but also be able to explain the basis of recommendation, so as to ensure the intelligibility of teacher evaluation and scheduling recommendations. Wang et al. studied the overall development of artificial intelligence in education and proposed that the application of artificial intelligence in education scenarios has expanded from a single recognition task to multiple directions such as learning analysis, personalized support, automatic feedback and management decision-making [11]. This review provides a macro reference for the modeling of teaching behavior data and the design of intervention mode. Baig and Yadegaridehkordi studied the application progress of ChatGPT in higher education, and proposed that the generative model has obvious expansion ability in auxiliary learning, content organization and interaction support, and at the same time it needs to maintain a prudent design in reliability and governance structure [12]. This conclusion has direct enlightenment significance for the introduction of generative auxiliary feedback in standardized training bases. Gao et al. studied the automatic evaluation system of text responses in higher education, and proposed that natural language processing and large language models are changing the way text feedback, subjective response scoring and formative evaluation are implemented [13]. The study provides a methodological source for the automated analysis of case discussion records, the text of instructor comments, and written feedback from trainees.To facilitate sorting out the correspondence between the existing research and the task of this paper, the relevant technical clues can be summarized as Table 1.

Table 1: Technical clues of related research and contents that can be used for reference in this paper

Reference	Research Focus	Adaptable Content
[10]	Review of explainable decision support systems	Constructing an intervention outcome explanation chain and its visualization basis
[11]	Review of educational artificial intelligence systems	Organizing teaching analysis tasks and indicator frameworks
[12]	Review of generative model applications in education	Designing interactive feedback and assistance prompt modules
[13]	Review of automated text evaluation systems	Processing mentoring texts, comments, and case feedback data

Airaj studied the application of ethical AI in higher education and proposed that the human-centered use of technology should simultaneously cover fairness, privacy protection and responsibility boundaries [14]. This study suggests that the system design for the improvement of teachers 'teaching ability should not only focus on the recognition accuracy, but also take into account the compliance expression and role boundaries of the evaluation process. Magalhaes Araujo and Cruz-Correia studied the mixed-method application of ChatGPT in medical informatics education, proposed that generative tools could be used as auxiliary resources for course interaction and learning support, and gave the design idea of prompts for teaching integration [15]. This study illustrates that intelligent tools in medical education scenarios are more suitable for embedding into specific teaching tasks rather than running independently from business processes. Holderried et al. studied a language model-driven simulated patient system with automatic feedback, and proposed that the model could provide immediate feedback and interactive response during history taking training [16]. This result shows that the question-answer chain, prompt chain and feedback chain in clinical teaching activities can be unified into a computable process. Burke et al. studied the scoring ability of the large language model on the free-text clinical records of medical students, and proposed that the model had strong quantitative discrimination ability in the evaluation of clinical texts [17]. This study provides a realistic basis for the automatic scoring of case analysis records, teaching comment records and formative evaluation texts in standardized training bases.

In terms of health data competency and medical information education, Doll et al. studied the health data-informed competency framework for clinical staff, and proposed that clinical staff should have the ability of data acquisition, data understanding and digital literacy transformation at the same time [18]. This point of view indicated that the analysis of teaching ability of teachers in standardized training bases could not be separated from the dimension of data ability, and teaching implementation and data understanding should be put into the same ability structure. Han studied the topics and trends of health informatics education research, and proposed that a research aggregation structure centered on digital health, medical information training and educational technology integration was forming in this field [19]. This finding provides the academic context for this paper to integrate clinical teaching, learning analytics, and intelligent intervention in the same model. Hersh reviewed the development process of online informatics education over the past 25 years, and proposed that the extensible, transferable and continuous iterative structure of online education could support complex professional training [20]. This conclusion suggested that the intervention system for standardized training bases should have the ability of modular deployment, continuous update and cross-scenario migration.

Based on the existing research, it can be seen that the current related achievements have formed a continuous technology chain from interpretable decision support, artificial intelligence in education, generative interactive feedback to health data ability training. Based on this basis, this paper defined the research entities as teachers 'teaching behaviors, teaching process states, students 'feedback results and intervention execution records, and constructed a multi-dimensional intervention model under a unified data representation, which formed a closed loop of teaching ability identification, strategy generation, task scheduling and result writeback.

3 Design and research on multidimensional intervention model of clinical teaching ability of teachers in general practice standardized training base

3.1 Feature representation model of multi-source clinical teaching behavior and teaching process

Clinical teaching in general practice training bases consists of outpatient guidance, ward rounds, case discussion, skill demonstration and stage feedback. Different activities have obvious differences in time density, task goal, interaction mode and evaluation diameter. If only classes, scores or brief conclusions are retained, the organizational stability, feedback timeliness, demonstration clarity and process collaboration of teachers 'clinical teaching ability are difficult to form computable representations. In order to make the teaching process into a unified analysis link, this paper organizes teaching logs, text comments, supervision records, task write-back information and stage evaluation results into multi-source observation objects, and completes feature splicing and status update in the same time window. Suppose that the original input of the TTH teaching activity consists of behavioral features, text features, process state features and result evaluation features, then the joint observation vector is defined as follows.

$$h_t = \left[x_t^{(b)} \parallel x_t^{(n)} \parallel x_t^{(s)} \parallel x_t^{(e)}\right] \tag{1}$$

where, h_t represents the joint observation vector of the t teaching activity, $x_t^{(b)}$ represents the behavioral characteristics composed of the frequency of ward rounds, the number of questioning rounds, the duration of teaching and the density of interaction, $x_t^{(n)}$ represents the semantic features encoded by the comment text, case summary and rectification instructions. $x_t^{(s)}$ represents the process state characteristics formed by task writeback delay, rectification state and supervision closed loop, $x_t^{(e)}$ represents the result characteristics composed of student rating, supervision opinion and stage evaluation, and the symbol $\parallel$ represents vector splicing. The function of this formula is to maintain the structural correspondence of multi-source data at the same time point, so that the ward round behavior, text feedback and process records can enter the subsequent calculation at the same time.

Static splicing alone is not sufficient to characterize the ability evolution in continuous teaching. The interrogation method in outpatient guidance, the demonstration rhythm in ward round, the feedback depth in case discussion and the correction intensity in skill training all have the characteristics of pre-and post-dependence. To this end, this paper introduces a gated update mechanism to jointly encode the historical state and the current observation. The update gate mainly determines the writing intensity of the current teaching activity to the overall state, and its expression is as follows:

$$z_t = \sigma(W_z[H_t \parallel g_{t-1}] + b_z) \tag{2}$$

$$r_t = \sigma(W_{r1}(Ph_t \odot g_{t-1}) + W_{r2}|Ph_t - g_{t-1}| + b_r) \tag{3}$$

Here, z_t represents the update gate vector of the t teaching activity, which is used to control the proportion of the current observation written to the state representation as a whole. r_t indicates the difference aware association gate vector, which is used to measure the local consistency relationship and offset degree between the current activity and the historical state.

H_t represents the joint observation vector formed by the concatenation of behavior features, text features, process state features and result evaluation features. g_{t-1} represents the state of the teaching process at the previous moment; P is the dimension mapping matrix, which is used to project the current observation into the feature space consistent with the historical state. W_z, W_{r1}, W_{r2} are weight matrices; b_z and b_r are bias terms; $\|$ indicates vector concatenation; $\odot$ for element-wise multiplication; $|\cdot|$ denotes the element-wise absolute value; Let $\sigma(\cdot)$ denote the Sigmoid activation function. Formula (2) judges to what extent the current teaching activity should update the existing state from the overall level, and formula (3) describes the matching strength and difference range between the current observation and the historical state from the fine-grained level. In this way, the continuous dependencies in outpatient instruction, teaching rounds, case discussion and skill demonstration can not only be preserved, but also identify local offsets between different stages.

After obtaining the overall writing control results and the difference awareness correlation results, the model further fuses the current observation and the historical teaching state to form a dynamic process representation that can simultaneously reflect the stage stability, local offset and feedback continuity. Therefore, the update process of the teaching state vector is defined as follows:

$$g_t = (1 - z_t) \odot g_{t-1} + z_t \odot \tanh(W_h h_t + U_h(r_t \odot g_{t-1}) + b_h) \tag{4}$$

Here, g_t represents the updated state of the teaching process at time t, W_h and U_h are the state mapping parameters, b_h is the bias term, $\odot$ represents element-wise multiplication, and $\tanh(\cdot)$ represents the nonlinear activation function. This formula maps the current observation information and the historical state after screening by the correlation gate into a unified space, so that the model can not only retain the stable characteristics in continuous teaching, but also identify the local fluctuations caused by the change of the rhythm of ward rounds, the change of the strength of feedback and the change of the speed of task advancement.

To ensure that the subsequent calculations have clear input boundaries, the core variables entering the model are organized in Table 2 in this paper. The four types of variables are not simply superimposed, but participate in state update, scene aggregation and portrait generation together in a unified time window.

Table 2: Composition and computational roles of multi-source clinical teaching behavior characteristics

Feature Category	Specific Variables	Data Source	Computational Role
Behavioral Execution Features	ward-round frequency, follow-up questioning turns, demonstration duration, interaction density	teaching logs, platform records	describing the intensity of teaching implementation
Text Semantic Features	comment themes, feedback completeness, terminology coverage	comment texts, case summaries	representing the quality of language-based guidance
Process State Features	task write-back delay, rectification completion rate, supervision closed-loop rate	task system, supervision records	describing process coordination
Evaluation Outcome Features	trainee scores, supervision evaluations, stage performance	rating forms, assessment system	reflecting stage-wise outputs

The contribution of different teaching scenes to teachers 'ability portraits is not consistent. The outpatient guidance can better reflect the ability of real-time question answering and explanation, the ward round can better reflect the ability of case integration and demonstration organization, the case discussion emphasizes the diagnosis and treatment reasoning and expression structure, and the skill training emphasizes the operation standard and correction feedback. In order to form a comparable representation of different scenes in the same framework, this paper further constructs a scene attention aggregation function:

$$\alpha_{t,k}=\frac{\exp\left(q^{\top}\tanh(W_a g_{t,k}+b_a)\right)}{\sum_{j=1}^{K}\exp\left(q^{\top}\tanh(W_a g_{t,j}+b_a)\right)},\quad c_t=\sum_{k=1}^{K}\alpha_{t,k}\,g_{t,k} \tag{5}$$

Here, $g_{t,k}$ represents the state representation of the k teaching scene at time t, $\alpha_{t,k}$ represents the attention weight of the corresponding scene, q and W_a are trainable parameters, b_a is the bias term, and c_t represents the core teaching representation after multi-scene aggregation. Through adaptive weight allocation, the system can automatically adjust the feature contribution proportion according to the performance differences of different teachers in specific scenes, thereby reducing the bias caused by a single activity type on the overall portrait.

The ability to teach depends not only on the intensity of behavior, but also on whether the language interpretation is consistent with the demonstration process. If the logical sequence of case explanation, question and response in ward round, and term explanation in skill teaching are not consistent with the actual operation rhythm, the final teaching effect will often have structural deviation. To this end, the semantic-behavioral consistency function is defined as follows:

$$m_t=\frac{v_t^{(n)}\cdot v_t^{(b)}}{\|v_t^{(n)}\|_2\|v_t^{(b)}\|_2}+\lambda J(y_t^{(n)},y_t^{(b)}) \tag{6}$$

where, $v_t^{(n)}$ represents the text semantic embedding vector, $v_t^{(b)}$ represents the behavior pattern embedding vector, and the first term uses cosine similarity to measure the directional consistency between the explanation content and the demonstration behavior. $J(\cdot)$ represents the matching function based on the label set, and $y_t^{(n)}$ and $y_t^{(b)}$ represent the text topic label and the action category label, respectively. Let λ be the balance coefficient. The meaning of this formula is that the semantic information and behavioral information are used to describe the teaching activity, so that the model can not only identify "what is said", but also measure "whether the process of doing is consistent with the said content".

After the multi-scenario aggregation and consistency calculation, the system also needs to compress the state results in the continuous time window into the profile output that can be invoked by the subsequent intervention strategy. Considering the baseline differences of different teachers in task load, teaching scenario and feedback rhythm, this paper constructs the comprehensive ability score and stage portrait function:

$$s_t=\omega_1\mathrm{Norm}(c_t)+\omega_2\mathrm{Norm}(m_t)+\omega_3\mathrm{Norm}(e_t)-\omega_4\mathrm{Norm}(d_t),$$

$$p_i=\mathrm{Softmax}\left(W_p[\mathrm{Mean}(S_i)\|\mathrm{Var}(S_i)\|\mathrm{Trend}(S_i)\|\mathrm{Comp}(S_i)]+b_p\right) \tag{7}$$

where, s_t represents the comprehensive ability score at stage t, $\mathrm{Norm}(\cdot)$ represents the standardized mapping, e_t represents the result evaluation from students and supervisors, d_t represents the load penalty term formed by feedback delay, task backlog and rectification lag, and ω_1 to ω_4 are the weight parameters. S_i represents the scoring sequence formed by the i

teacher within an evaluation window, $\mathrm{Mean}(\cdot)$, $\mathrm{Var}(\cdot)$, $\mathrm{Trend}(\cdot)$ and $\mathrm{Comp}(\cdot)$ represent the mean, fluctuation, trend and structural integrity respectively, and p_i represents the profile distribution of teachers in the dimensions of stable teaching, feedback response, process collaboration and demonstration expression. The first half of the formula completes the comprehensive scoring under a unified scale, and the second half further compreses the scoring sequence within the time window into a multi-dimensional portrait, so that the subsequent module can be directly called.

The feature representation model formed in this way retains the temporal changes of teaching activities and the structural differences of different teaching scenarios, and the subsequent intervention strategy generation can directly call these state results to complete individual identification and task scheduling. Compared with the methods that only rely on questionnaire scores or stage total reviews, the model integrates teaching behavior, text feedback and process closure loop into the same calculation chain, which can reduce the information compression caused by a single indicator and provide a unified input for subsequent system deployment. The model also retains the window update and index expansion interface, which is convenient for different training bases to complete parameter adaptation combined with local scenes.

3.2 Teaching intervention strategy generation and adaptive scheduling algorithm

After the multi-source teaching behavior representation is completed, the intervention module also needs to convert the portrait results into a task allocation scheme. The promotion of teachers in general practice standardized training bases is not a simple sorting, but a matching of training content and supervision intensity for different teachers according to the performance differences in outpatient guidance, teaching rounds and skill teaching. In order to make the policy generation computable, this paper maps teacher states, resource constraints and intervention goals into a unified decision space. To illustrate the overall computational link of instructional intervention strategy generation and adaptive scheduling, the algorithm flow is summarized as Fig. 1 in this paper. The left input of the figure includes the teacher portrait vector, the ability short board label, the resource capacity constraint and the feedback delay information. The middle part completed candidate action generation, action benefit evaluation, resource conflict resolution and periodic scheduling update in turn. The right output forms the individual intervention task, the group scheduling result, and the basis for the next round of state correction. Instead of statically sorting a single action, the process organizes portrait recognition, task matching, resource allocation and result writeback into a continuous calculation process, so that the intervention suggestions can maintain executability and updatability in the real teaching scene of the standardized training base.

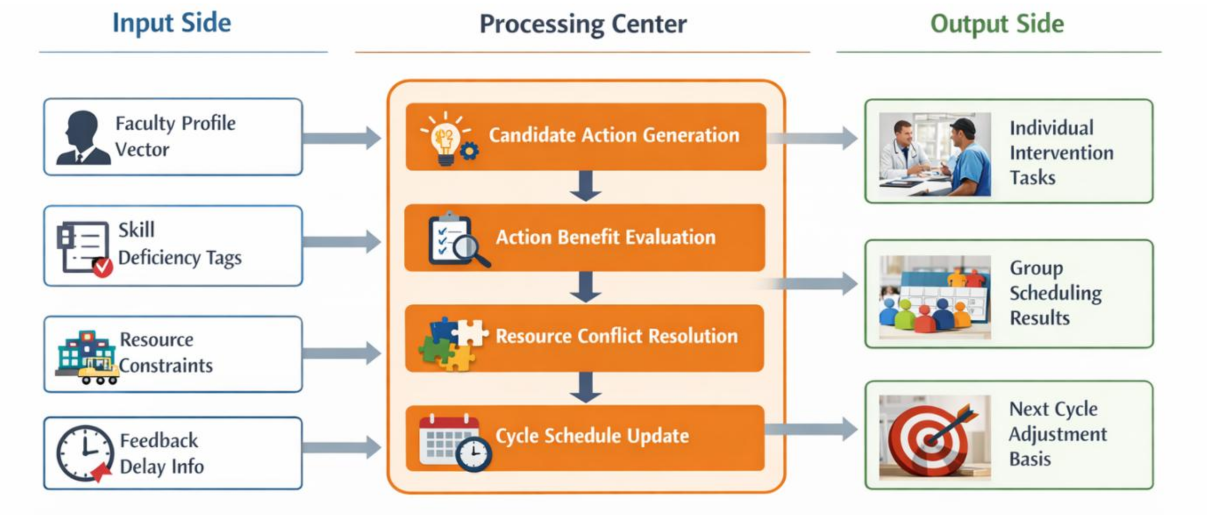

Figure 1: Process of instructional intervention strategy generation and adaptive scheduling algorithm

In the candidate action generation phase, the system constructs the intervention set according to the portrait results, and the action scoring function is defined as follows.

$$a_{i,k}^{t} = \sigma(w_1^{T} p_i^{t} + w_2^{T} u_k + w_3^{T} r_t + (p_i^{t})^{T} H_k r_t + b_a) \tag{8}$$

where $a_{i,k}^{t}$ represents the initial score of the i teacher selecting the k intervention action at time t, p_i^{t} represents the teacher profile vector, u_k represents the action type embedding, r_t represents the resource constraint vector in the current window, H_k represents the interaction matrix between actions and resources, and w_1, w_2, w_3 and b_a are the parameters to be learned. This formula integrates portrait information, action attributes and resource conditions into the same scoring framework to screen out candidate actions.

Action scores alone do not form a final plan. The effects of different intervention actions on the improvement of teaching ability were not consistent, and the benefits and costs of short-term workshop, case review, demonstration observation and fixed-point supervision were different. To this end, this paper further constructs the benefit evaluation function:

$$R_{i,k}^{t} = \alpha \Delta q_{i,k}^{t} + \beta \ln(1 + \mu_{i,k}^{t}) - \gamma \rho_{i,k}^{t} - \delta \tau_{i,k}^{t} \tag{9}$$

where, $R_{i,k}^{t}$ represents the comprehensive income of the i teacher after performing the k action, $\Delta q_{i,k}^{t}$ represents the expected ability gain, $\mu_{i,k}^{t}$ represents the matching degree between the task and the current ability shortboard, $\rho_{i,k}^{t}$ represents the resource consumption intensity, $\tau_{i,k}^{t}$ represents the feedback delay cost, α, β, γ, δ are the balance coefficients. This puts the improvement and execution cost on the same scale.

When multiple teachers compete for limited resources at the same time, the system also needs to deal with action conflicts and scheduling constraints. In this paper, a constrained objective is used to construct a global scheduling function to maximize the overall revenue and control the risk of resource overallocation in a single period. The objective function is written as follows.

$$\max_{X^t} \sum_{i=1}^{N} \sum_{k=1}^{K} x_{i,k}^t R_{i,k}^t - \lambda \sum_{m=1}^{M} \left[\max\left(0, \sum_{i=1}^{N} \sum_{k=1}^{K} x_{i,k}^t g_{k,m} - c_m^t \right) \right]^2 - \xi \sum_{i=1}^{N} \left(\sum_{k=1}^{K} x_{i,k}^t - 1 \right)^2 \quad (10)$$

where $x_{i,k}^t$ denote whether the k intervention action is assigned to the i teacher, $g_{k,m}$ denote the demand of action k for the m resource, c_m^t denotes the available capacity of the m resource in the cycle, and λ and ξ are penalty coefficients. The former term of this equation accumulates overall revenue, the second term suppresses resource overallocation, and the third term constrict the uniqueness of actions in a single period.

After the completion of the action filtering in the cycle, the system also updates the scheduling state for the next round. Considering that the intervention effect has lag and accumulation, this paper introduces an adaptive state update function:

$$p_i^{t+1} = \eta p_i^t + (1 - \eta) \tanh\left(W_p p_i^t + U_p x_i^t + V_p f_i^t + b_p\right) \quad (11)$$

where, p_i^{t+1} represents the updated profile of the i teacher in the next cycle, η represents the historical state retention coefficient, x_i^t represents the set of intervention actions that have been performed in this round, f_i^t represents the feedback results after execution, W_p, U_p, V_p and b_p are state correction parameters. This formula integrates the existing ability basis, the current execution task and the result feedback into the next round of portrait update.

Through the above calculation process, the teaching intervention strategy no longer stops at experience assignment, but forms a computable scheduling result according to teacher portraits, action benefits and resource constraints. The algorithm can give targeted training tasks at the individual teacher level, complete scheduling coordination and resource allocation at the base level, and continuously revise the portrait status of the next cycle according to the execution feedback. In this way, the subsequent system modules call not only the static scoring results, but the complete decision output containing task priority, resource occupancy relationship, and phase update information.

4 Multi-dimensional intervention mechanism of clinical teaching ability of general practice standardized training base teachers based on intelligent computing

After completing the construction of teacher portraits and the design of scheduling algorithm, the system also needs to transform the recognition results into an executable, writable, and amendable intervention mechanism. The teacher promotion in general practice standardized training base is not a simple superposition of single training task, but a continuous operation process composed of ability gap identification, task combination configuration, base resource coordination and execution feedback correction.

Therefore, on the basis of the above representation model and scheduling algorithm, this paper constructs a multidimensional intervention mechanism for the standardized training base scenario, and organizes it into a process as shown in Fig. 2. The left input side of the figure includes teacher portraits, target ability templates, resource maps and historical feedback records. In the middle part, the capability gap calculation, intervention combination generation and collaborative correction were completed in turn. The right output forms the basis of individual intervention plan, base execution plan and state correction in the next cycle. Instead of sorting the existing scoring results repeatedly, the gap characterization, task organization, resource coordination and feedback are written back to the same intelligent computing link.

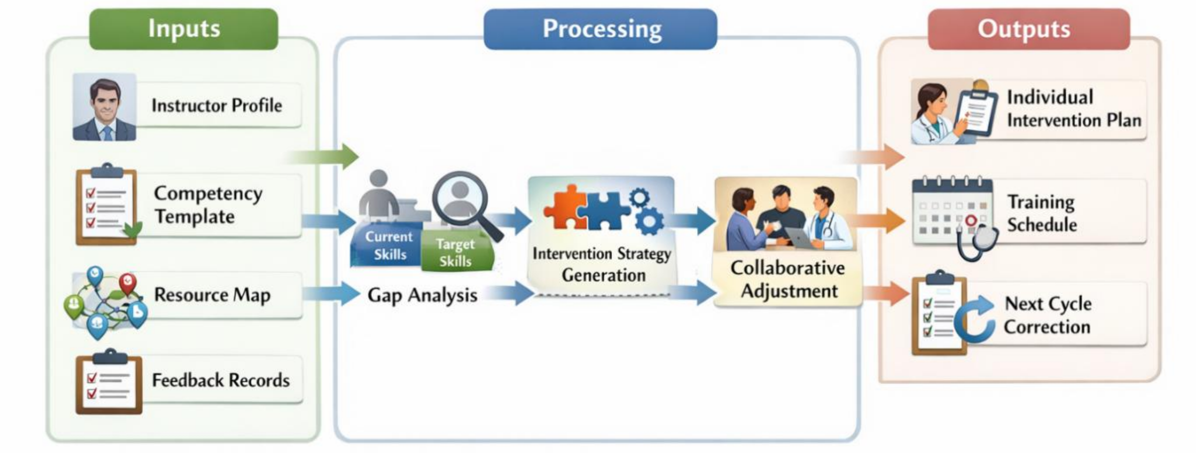

Figure 2: The process of multi-dimensional intervention mechanism of clinical teaching ability of teachers in general practice standardized training base based on intelligent computing

In order to map current teaching status to intervention needs, this paper first defines the ability gap intensity function. Instead of directly judging by a single score, this function compares the degree of structural shift between the current profile and the target template, and the expression is as follows:

$$d_i^t = \sqrt{(p_i^t - p^*)^\top M (p_i^t - p^*)} + \kappa u_i^t \tag{12}$$

Among them, d_i^t represents the ability gap intensity of the i teacher in the t period, p_i^t represents the current profile vector, p^* represents the target ability template preset by the base, M is the dimension weighting matrix, which is used to control the contribution intensity of different ability dimensions in the gap calculation, and u_i^t represents the uncertainty term formed by student feedback fluctuation, supervision inconsistency and task delay. Let κ be the equilibrium coefficient. The first half of the equation describes the geometric deviation between the current state and the target state, and the second half complements the process instability factors, so that the system can identify not only the size of the gap, but also whether the deviation is accompanied by obvious fluctuations.

After obtaining the gap strength, the system also needs to form the targeted intervention combination from the candidate task library. Considering that different tasks have differences in training direction, execution cycle and resource occupation, this paper further constructs the combined allocation probability function as follows:

$$\pi_{i,k}^t = \frac{\exp\left(\theta_1 c_k^\top G m_i^t + \theta_2 \nu_{i,k}^t - \theta_3 \chi_{i,k}^t\right)}{\sum_{j=1}^{K} \exp\left(\theta_1 c_j^\top G m_i^t + \theta_2 \nu_{i,j}^t - \theta_3 \chi_{i,j}^t\right)} \tag{13}$$

where $\pi_{i,k}^t$ represents the probability that the i teacher is assigned to the k intervention task in the t cycle, m_i^t represents the ability short board vector, c_k represents the task ability coverage vector, G is the short board-task mapping matrix, $\nu_{i,k}^t$ represents the adaptability of the task to the current teaching scene, $\chi_{i,k}^t$ represents the repetition degree of similar tasks in the recent past. The parameters θ_1, θ_2 and θ_3 are the adjustment parameters. This formula puts short board coverage, scene adaptation and repetition suppression in a unified allocation framework, so that tasks such as workshop, case review, demonstration observation and fixed-point supervision are no longer pushed in a fixed order, but form a dynamic combination according to the differences in current portraits.

Through the above mechanism, the intervention link consists of front-end identification, mid-stage cooperation, and back-end writeback to form a closed loop. The capability gap function is responsible for characterizing the structural deviation between the current portrait and the target template, and the combination allocation function is responsible for mapping the short board into an executable task. The system then completes the execution correction by combining the base resource capacity, teaching period and supervision schedule, and writes the student feedback, supervision evaluation and task records back to the next cycle status update. This multi-dimensional intervention mechanism can not only output targeted training programs at the individual level, but also maintain the continuity and consistency between task scheduling, resource allocation and feedback correction at the base level.

5 Design of clinical teaching ability improvement system for general practice standardized training base teachers based on decision support framework

The clinical teaching ability improvement system for teachers in general practice standardized training base is not a simple display of scoring results, but a unified decision support framework that organizes data access, status recognition, task generation, execution tracking and result writeback. Teachers' teaching activities cover outpatient guidance, teaching rounds, case discussion, skill teaching and stage feedback. The data sources have the characteristics of heterogeneous timing, different granularity and feedback delay, so the system design needs to ensure clear structure, stable service and smooth strategy call at the same time. Based on this requirement, the system is divided into data access layer, capability analysis layer, decision service layer and interactive application layer, and logs, texts, forms and supervision records are imported into the shared data bus through a unified interface.

In the process of system implementation, the intervention request needs to complete priority merging after entering the service center to ensure that the resources can respond to the task first. To this end, we define the request priority function as follows:

$$\Pi_i^t = \frac{\exp(\alpha_1 d_i^t + \alpha_2 \varepsilon_i^t + \alpha_3 \rho_i^t - \alpha_4 \tau_i^t)}{1 + \exp(-\alpha_5 \kappa_i^t)} \tag{14}$$

Here, Π_i^t represents the priority index of the i intervention request at time t, d_i^t represents the strength of the capacity gap, ε_i^t represents the urgency of the task, ρ_i^t represents the resource accessibility, τ_i^t represents the cost of response delay, κ_i^t represents the risk amplification term caused by teaching risk, student feedback fluctuation and task backlog, and α_1 to α_5 are regulatory parameters. The equation jointly maps gap, urgency, resource status and risk items into the same priority space, and the requests with high gap and urgency can be sent to the execution queue faster, while the requests with high delay cost will get additional correction under the effect of risk items. Therefore, the system can unify the scheduling rules, message queues and Kanban alerts under the same ranking basis.

After the prioritization is completed, the system also needs to decide the proportion of diversion between different service modules. Due to the differences in the execution cycle, manual participation and result writing methods among case review, fixed-point supervision, short training workshop and demonstration observation, a single routing method cannot maintain the overall throughput stability. Based on this, this paper further constructs the service allocation function as follows:

$$\Gamma_{i,k}^{t}=\frac{\exp(x_i^{t\top}Ws_k^t-\beta_1 l_k^t+\beta_2 h_k^t)}{\sum_{j=1}^{K}\exp\left(x_i^{t\top}Ws_j^t-\beta_1 l_j^t+\beta_2 h_j^t\right)} \tag{15}$$

where $\Gamma_{i,k}^{t}$ represents the execution probability that the i request is assigned to the k type of service node, x_i^t represents the request feature vector, s_k^t represents the capability description vector of service node, W is the mapping matrix matching request and service, l_k^t represents the current load of the node, h_k^t represents the historical execution success rate of the node, and β_1 and β_2 are the balance coefficients. This formula takes the request attributes, node capabilities, real-time load and historical execution effect into the offloading calculation, so that the system can maintain service adaptability under concurrent conditions and reduce the impact of local node backlog on the overall response efficiency.

To illustrate the system composition relationship, the overall structure is summarized as Fig. 3 in this paper. In the figure, the bottom layer is the multi-source data access module, the middle part is the feature calculation, portrait update, intervention generation and scheduling correction module in turn, and the top layer includes three application entrances: management end, supervision end and teacher end.

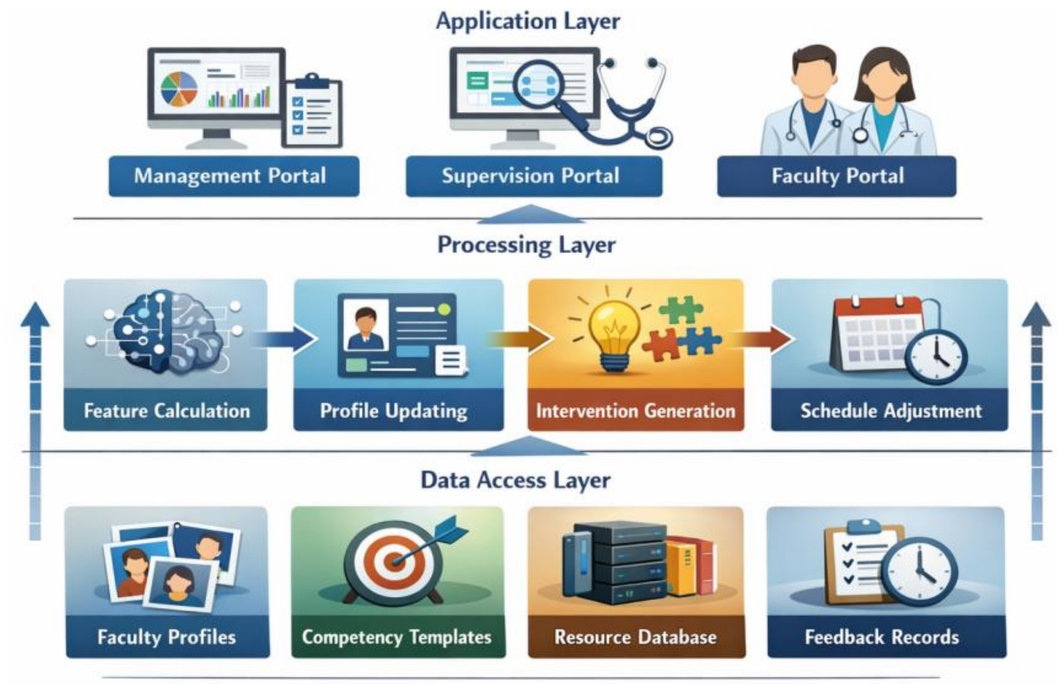

Figure 3: The structural framework of the clinical teaching ability improvement system for general practice standardized training base teachers based on the decision support architecture

According to the above architecture, the front-end of the system uses visual pages to organize teacher portraits, task lists and process alarms, the back-end uses a service-oriented deployment method to connect the feature calculation module, intervention engine and plan management module, and the database layer implements table storage and index management for logs, forms, texts and scheduling results. After this design, the improvement of teachers 'ability is no longer limited to offline evaluation, but can complete the continuous operation of recognition, dispatch, execution, review and writeback in a unified platform, which provides the implementation basis for performance testing and system testing in subsequent experiments.

6 Experimental results and analysis

6.1 Multidimensional intervention model performance testing

The performance of the proposed multi-dimensional intervention model was tested on a dataset consisting of 126 teachers from 8 general practice standardized training bases. The experimental data included 18640 teaching behavior records, 4320 student feedback information and 1260 structured evaluation forms. Compared with the methods that only rely on stage scoring or fixed rule judgment, the proposed model can simultaneously process three types of information, teaching behavior, text feedback and task writeback, and complete state recognition, short board location and intervention generation in a unified computing chain. Therefore, under the condition of the coexistence of multiple scenarios such as outpatient guidance, teaching rounds, case discussion and skill teaching, the model output can more stably reflect the dynamic changes of teachers 'clinical teaching ability.

Based on the trend analysis, this paper further evaluates the model from three aspects: recognition accuracy, comprehensive discrimination ability and response efficiency. To ensure the validity of the comparison, three control groups of rule scoring method, static weighted model and the proposed model are set up in the experiment, and the main results are shown in Table 3. Table 3 shows that the proposed model performs best in the three core indicators of Accuracy, F1-score and average response delay, in which the recognition accuracy reaches 93.1%, the F1 value reaches 91.8%, and the average response delay is controlled at 1.4s, which is consistent with the core experimental results in the abstract. At the same time, the AUC of the proposed model reaches 0.947, indicating that the model still has good discrimination ability under different threshold conditions.

Table 3: Performance comparison of different methods on the task of instructional intervention identification

Method	Accuracy / %	F1-Score / %	AUC	Average Response Delay / s
Rule-based Scoring Method	84.7	82.9	0.861	2.8
Static Weighted Model	88.5	87.1	0.903	2.1
Proposed Method	93.1	91.8	0.947	1.4

In order to observe the degree of fit between the model output and the real state, this paper counted the change trend of the predicted results and the actual results in 10 consecutive evaluation cycles, as shown in Fig. 4. The actual results of 10 cycles are 71.3, 73.0, 74.8, 76.2, 75.4, 78.9, 82.1, 84.0, 83.2 and 85.1, and the predicted results are 66.3, 68.4, 70.5, 72.2, 71.6, 75.4, 78.9, 81.1, 80.3 and 82.3, respectively. The average deviation is 4.34 for the first five cycles and decreases to 3.06 for the last five cycles, resulting in an overall mean absolute error of 3.7, with the largest deviation occurring in the first cycle, which is 5.0. In the figure, there is a certain distance in the first half of the two curves, but the direction of change is consistent. After entering the sixth cycle, the fit between the predicted curve and the actual curve is significantly improved, and the deviation has stabilized at about 3 points from the eighth to the tenth cycle. This shows that with the accumulation of teaching process data and feedback records, the multi-dimensional intervention model is more stable in identifying the real teaching state, and has a better tracking ability for stage fluctuations.

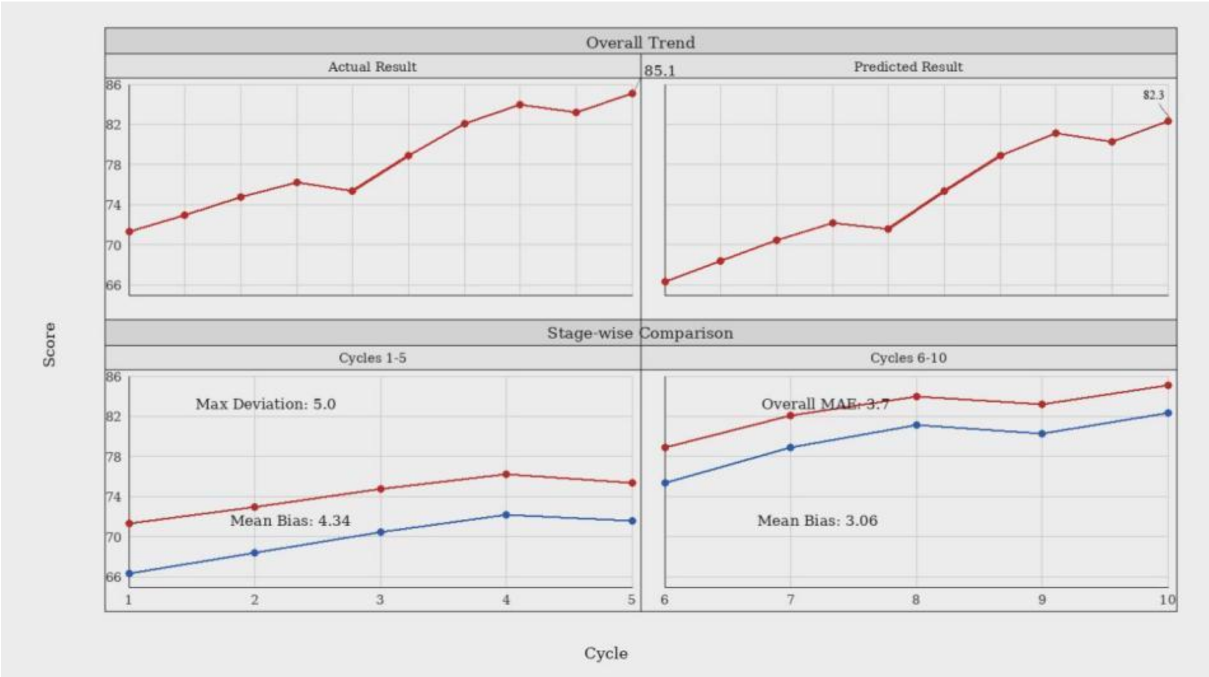

Figure 4: Comparison plot between predicted and actual results of multidimensional intervention patterns

From the comparison results, the rule scoring method is weak in identifying the boundary samples, and it is easy to classify the teachers with stable organization but insufficient feedback into the same level. Although the static weighted model can alleviate some of the offset, its adaptability to multi-scene switching samples is still limited. Since the temporal behavior, text feedback and process records are incorporated into the state update, the proposed model has stronger discriminative power in complex teaching scenarios. The test results show that the mean absolute error of the model in continuous evaluation is 3.7, and the stage fluctuation variance is 0.012, indicating that the model also maintains good performance in terms of output stability. In general, the multidimensional intervention mode is superior to the control methods in recognition accuracy, trend tracking ability and real-time response efficiency, which provides a reliable model foundation for subsequent system testing and platform deployment.

6.2 System test of improving the clinical teaching ability of teachers in standardized training bases

The system test was used to verify the data access, task distribution, result writeback and interactive response capabilities of the constructed platform in the standardized training scenario. Unlike model performance testing, which focuses on identification accuracy, this section focuses more on the functional integrity, scheduling stability, and feedback efficiency of the system in continuous operation states. The test environment is deployed in a three-tier service architecture, the bottom layer is the log library, text library and evaluation form library, the middle layer is the feature calculation service, intervention engine and scheduling management service, and the upper layer is the management end, supervisor end and teacher end. The test objects were the teaching records of 126 teachers from 8 general practice training bases, and four business flows including outpatient guidance, teaching rounds, case discussion and skill teaching were continuously imported to verify the operation effect of the system under the condition of multi-task concurrency.

In the functional test phase, the system first checks whether the multi-source data access and state writeback process are stable. Test results show that teaching logs, text comments, supervision records and task execution information can be parsed and stored into the database through a unified interface, the field mapping accuracy reaches 98.6%, and the cross-module writeback success rate reaches 97.9%. Fig. 5 shows the response delay distribution of different service modules. It can be seen from the figure that the response time of teaching log access and form update mainly concentrates between 0.8 s and 1.2 s, and the time consumption of text analysis and scheduling generation is higher, but the overall control is within 2.0 s. There is no blockage in the management end and the supervisor end under the condition of high frequency query, which indicates that the system maintains good transmission stability between data access and service invocation.

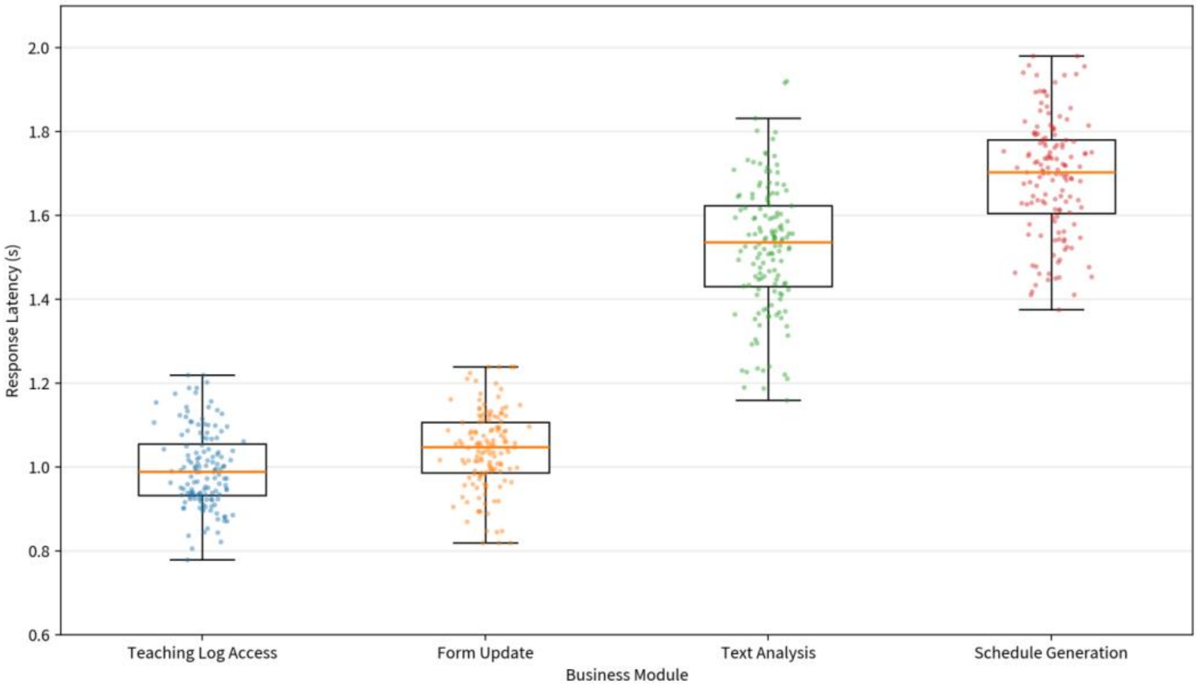

Figure 5: Response time delay distribution of each module of the clinical teaching ability improvement system for teachers in standardized training bases

In order to further verify the influence of the key modules of the system on the overall performance, this paper sets up an ablation experiment to perform stripping tests on the feature calculation module, intervention engine, scheduling correction module and feedback writeback module respectively, and the results are shown in Table 4. Table 4 shows that the system recognition accuracy decreases most obviously after removing the feature calculation module, indicating that the front-end state extraction is still the basis for the stable operation of the whole platform. After removing the intervention engine, the task matching rate and the stage completion rate decreased simultaneously, indicating that the regular dispatch could not replace the intelligent generation. After removing the scheduling correction module, the resource conflict rate increases. Although the system can still operate, the collaborative efficiency at the base level is significantly weakened. When the feedback writeback module is removed, the ability of state correction in the next cycle is reduced, and the operation stability is weakened.

Table 4: Results of ablation experiments on key modules of the system

Module Configuration	Accuracy / %	Task Matching	Resource Conflict	Stage Completion

		Rate / %	Rate / %	Rate / %
Complete System	93.1	91.6	4.8	90.9
Without Feature Computation Module	88.2	86.4	6.7	84.3
Without Intervention Engine	89.1	83.8	6.1	85.1
Without Scheduling Correction Module	91.0	89.3	10.4	87.6
Without Feedback Write-back Module	90.3	88.7	5.9	86.8

In the execution link test, we further observe the cooperative performance between task distribution and state update. In 10 consecutive test cycles, the system generated a total of 842 intervention tasks, including 214 case review tasks, 176 demonstration observation tasks, 193 short training workshop tasks, and 259 fixed-point supervision tasks. The average confirmation time is 1.6 s, and the completion rate of writing back the execution results is 96.8%. Fig. 6 illustrates the 3D scatter between task gain, resource occupancy, and feedback completion rate. The scatter points form a more concentrated distribution cluster in the middle and high profit area, and the resource occupancy rate mainly falls between 0.52 and 0.78, indicating that the system improves the task pertinence while there is no obvious resource crowding. Some low-payoff points are mainly concentrated on tasks with high repetition, which is consistent with the repetition suppression mechanism in the strategy module, and also shows that the platform can gradually weaken inefficient allocation through continuous iteration.

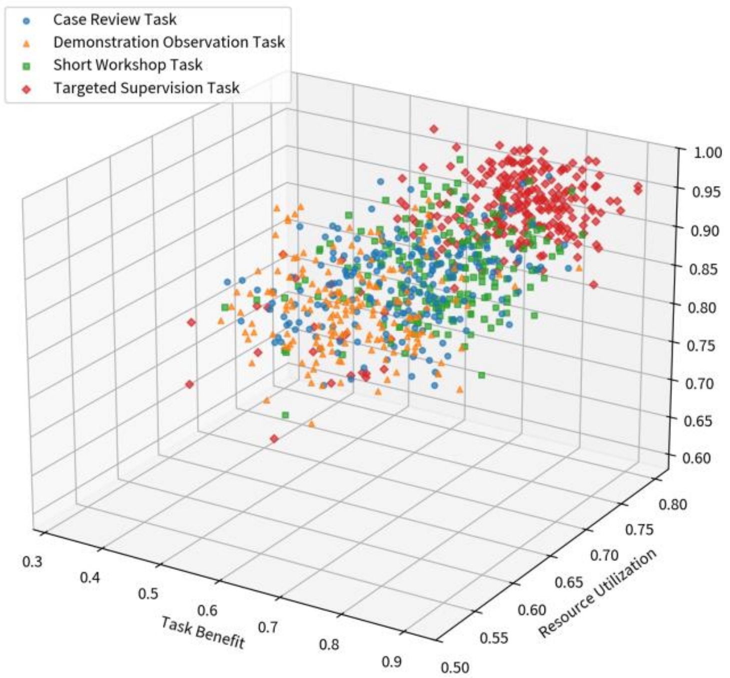

Figure 6: 3D scatter plot of intervention task benefit, resource occupancy, and feedback completion rate

In the user-side test, this paper continues to investigate the interactive performance of three types of terminals. The management end focuses on the global test kanban board, plan retrieval and alarm prompts, the supervision end focuses on the test task review, rectification tracking and opinion writing back, and the teachers end focuses on the test task reception, progress confirmation and result viewing. Fig. 7 shows the change trend of successful access rate of three types of terminals under different concurrency scales. When the number of concurrent users increased from 20 to 120, the successful access rate of the management side decreased from 99.1% to 96.4%, the supervisor side decreased from 98.8% to 95.9%, and the teacher side decreased from 99.3% to 96.7%, maintaining a high level overall. Combined with the log record analysis, the slight decrease in the success rate mainly comes from the queuing of the text parsing service under high concurrency, while the page rendering and task viewing functions do not show abnormal interruption.

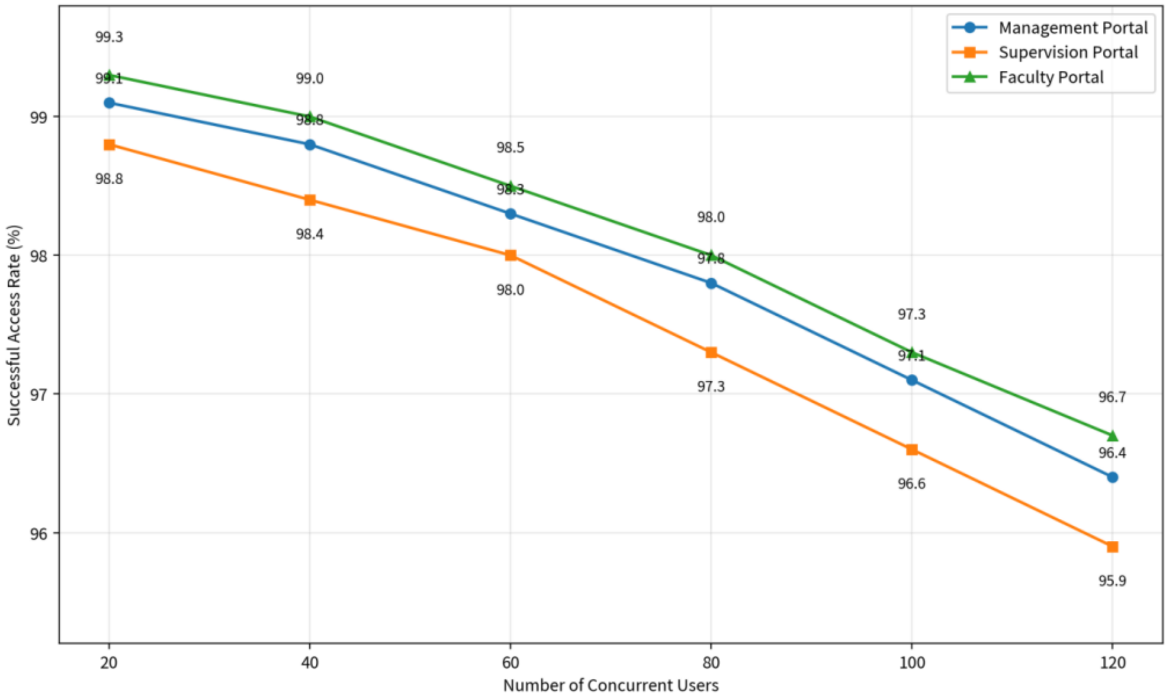

Figure 7: Graphs of the change of successful access rates of three types of terminals under different concurrency scales

In summary, the system has been able to maintain high operational integrity under the conditions of concurrent access to multi-source data, continuous generation of intervention tasks, dynamic adjustment of resource scheduling and stable writeback of feedback results. Compared with the platform that simply displays scoring results, the system in this paper emphasizes the closed-loop connection between recognition, dispatching, execution and correction, so it shows stronger continuous service ability in the real training base scenario. The system test results show that the designed decision support architecture can not only carry the algorithm output of multi-dimensional intervention mode, but also stably transform these outputs into executable teaching support processes, which provides a reliable implementation basis for subsequent promotion and application.

7 Conclusions

Focusing on the task of improving the clinical teaching ability of teachers in general practice standardized training bases, this paper constructed a multi-dimensional intervention model for real teaching scenarios and its decision support implementation path. A total of 126 teachers from 8 general practice training bases were selected as the research objects, and 18640 teaching behavior records, 4320 student feedback information and 1260 structured evaluation forms were collected. The multi-source behavior characteristics representation, intervention strategy generation, adaptive scheduling and system deployment were completed. Experimental results show that the recognition accuracy of this model reaches 93.1%, the F1 value reaches 91.8%, the AUC reaches 0.947, and the average response delay is controlled at 1.4 s. It can transform the scattered teaching records, feedback information and scheduling results into a continuous and computable teaching support process.

There are still some limitations in this paper. The existing models are mainly based on structured logs, text comments and stage evaluation, which still do not fully cover the details of audio and video teaching, real-time interactive tone and implicit teaching behaviors in complex clinical situations. Although the system has formed a closed loop of recognition, dispatch, execution and writeback, the migration effect of some indicators is still affected by the differences in cross-base data standards, and the ability of fine-grained semantic understanding and automatic interpretation still needs to be enhanced.

Follow-up research will continue to be carried out from three directions: multimodal input, interpretable computing, and cross-base deployment. Speech recognition, visual analysis, and clinical scene perception can further expand the input of teaching evidence and enhance the ability to characterize the demonstration process and interaction quality. The refinement of the interpretable computing module helps to present the key rationale and path sources for intervention recommendations. The combination of federated modeling and lightweight deployment is conducive to the realization of joint training and local call under the premise of ensuring data security, which enhances the generalization ability and application adaptability of the system.

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